

# A Framework for Daily Mental Attitude Monitoring of Workers

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**Abstract**—Monitoring mental health is important for people at work, as well as in other aspects of our lives. This is because mental states affect workers’ health and labor productivity. Many governments in developed countries are working to support workers’ mental health, but previous methods are based on questionnaires and interviews, which are not suitable for daily use. Therefore, we propose “Work Attitude PLR (Personal Life Record) collection platform” that can continuously estimate and record “Work Attitude” (a composite measure of work engagement and recovery experience, etc.) using multimodal information. In this paper, we describe the framework of our proposal and show the performance of the estimation model that positively suggest the feasibility of our method.

**Index Terms**—Work style reform, Stress, Work engagement, Recovery, Multi-modal information, Emotion recognition

## I. INTRODUCTION

It is important for workers to maintain a healthy mental state to ensure labor productivity. For this reason, many developed countries, including Japan, where many workers are engaged in long hours of work and suffer from poor health and high levels of stress, are monitoring workers’ mental health and trying to create healthier work environments. However, the monitoring methods currently used in practice are interviews and questionnaires [1], and are not intended to be used on a daily basis.

With the spread of smartphones, there has been growing interest in using mobile devices to monitor users’ mental states and promote self-care [2], and methods for estimating psychological states using smart devices have been proposed [3] [4]. However, many previous works use information from contact devices such as smartwatches, which places a high burden on the user. In addition, most studies have focused on negative indicators such as stress and depression, and not on positive indicators of worker well-being. Even when stress is present, it is considered not to be a problem when workers are highly motivated to work and recover from stress, so both positive and negative indicators need to be included in order to maintain workers’ mental health.

Therefore, we developed the Work Attitude scale, which can evaluate both positive and negative mental attitudes of workers toward their work. We also propose a “Work Attitude PLR (Personal Life Record) collection platform” that can continuously estimate Work Attitude based on multimodal information obtained from only smartphones.

TABLE I  
WORK ATTITUDE SCALES

Measurement category	Scale	Summary
Recovery Experience [5]	RE1	Psychological detachment
	RE2	Relaxation
	RE3	Mastery experiences
	RE4	Control during leisure time
Recovery State [6]	RS1	Feeling physically refreshed
	RS2	Feeling mentally refreshed
	RS3	Sleep efficiency
Work Engagement [7]	WE1	Vigor
	WE2	Dedication
	WE3	Absorption

## II. PROPOSAL METHOD

### A. Work Attitude

We developed the Work Attitude scale with the cooperation of clinical psychologists to assess the mental state of workers from both positive and negative perspectives. The Work Attitude scale is a composite of three existing scales: Recovery Experience [5], Recovery State [6], and Work Engagement [7]. These scales are summarized in Table I.

### B. Work Attitude PLR collection platform

Fig. 1 shows an overview of Work Attitude PLR collection platform. The system consists of a smartphone and a server.

Smartphones collect activity data and selfie video data (about 10 seconds). The activity data are the distance traveled and the number of steps taken. The selfie video data is the worker’s brief message about how he or she is feeling at that moment. The smartphone sends these data to the server.

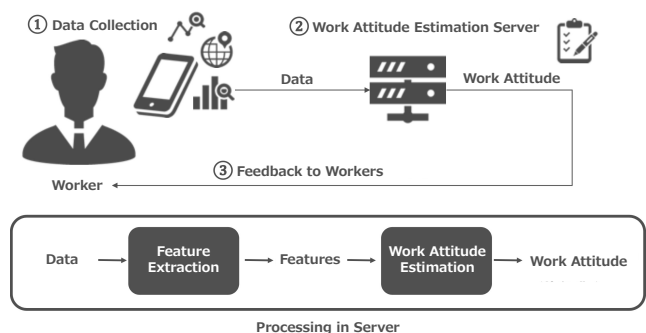


Fig. 1. Overview of Work Attitude PLR collection platform.

The server extracts features from the received data and inputs them to the Work Attitude estimation model. In feature extraction, emotion values are calculated from each of the face images, voice, and text (the speech content) channel of the selfie video data using the Face API (Microsoft), Empath API (Empath), and Cotoha API (NTT Communications), respectively. The features of the face image channel are the mean, median, variance, and maximum of the emotion values for each of the 5 images extracted from the video. As a result, 78 types of data are used as features. The estimation model is constructed using Random Forest. The output Work Attitude is recorded in a database as a PLR and fed back to the worker.

### III. EXPERIMENTS & RESULTS

We evaluated the performance of our estimation model.

9 male subjects participated in the 2-week experiment. Subjects were asked to take video only and to act as usual otherwise. As a result, a total of 155 samples were obtained. In addition, subjects answered the Work Attitude value used as the ground-truth in questionnaires after the video recording. The results were merged into 2 classes for RS3 and into 3 classes for the other scales to ensure a sufficient sample size.

The model was evaluated by leave-1 sample-out cross-validation in two ways: with all features and with feature selection. Feature selection was based on Gini importance. The estimation was performed sequentially by adding features one by one, starting with the most important features, and the subset of features with the best performance was adopted.

The F1 scores for each scale of the Work Attitude estimation model are shown in Fig. 2. The dashed bars indicate the F1 score calculated by interpolating the corresponding precision as 0 because there were no cases classified into a particular class. The F1 score of RE1 was significantly higher than the chance level. For RE2, RS1, and RS2, significance was shown only when features were selected.

In addition, Fig. 3 shows the frequency distribution of each feature selected. Here, different trends were observed for each scale. This suggests that our proposed method using multimodal information is suitable for Work Attitude estimation.

### IV. CONCLUSION

For daily mental attitude monitoring of workers, we proposed Work Attitude, which can represent both positive and negative perspectives, and Work Attitude PLR collection platform, which estimates, stores, and feeds back Work Attitude.

Experimental results showed significantly higher F1 scores for several measures, and feature selection further enhanced this performance. The frequency distributions of the selected features, which differ from scale to scale, indicate the effectiveness of using multimodal information in our method.

In the future, we will collect large-scale data to ensure a sufficient number of samples, and then conduct a demonstration experiment using data that has been processed by re-sampling.

### ACKNOWLEDGMENT

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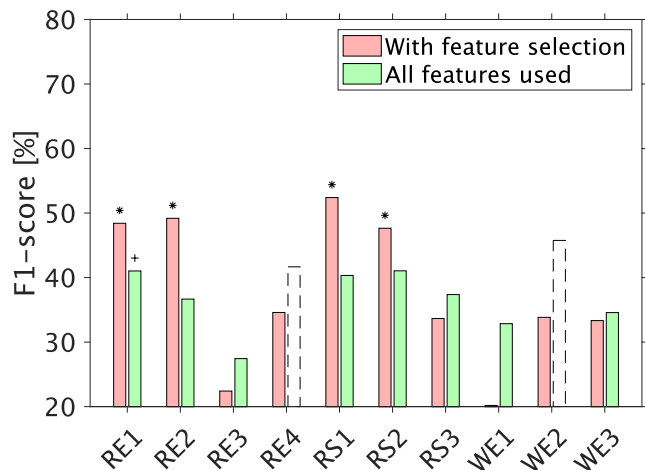


Fig. 2. Estimation performance. (Permutation test, uncorrected, \*:  $P < 0.01$ ; +:  $P < 0.05$ )

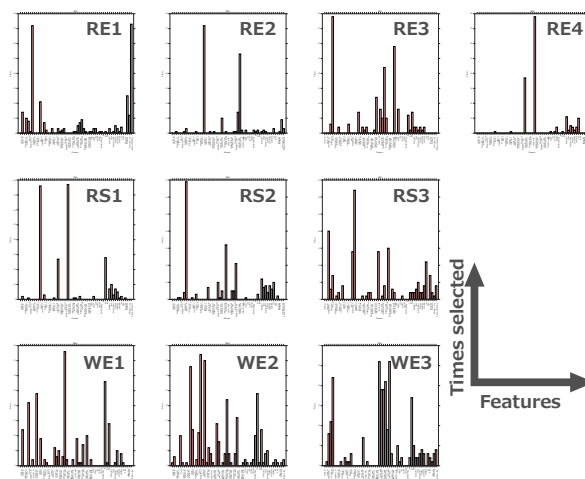


Fig. 3. Distribution of the number of times each feature was selected.

### REFERENCES

- [1] P. D. Harvey, B. R. Greenberg, and M. R. Serper, "The affective lability scales: development, reliability, and validity," *Journal of clinical psychology*, vol. 45, No. 5, pp. 786–793, 1989.
- [2] V. P. Cornet, and R. J. Holden, "Systematic review of smartphone-based passive sensing for health and wellbeing," *Journal of Biomedical Informatics*, vol. 77, pp. 120–132, 2018.
- [3] C. Amenomori, T. Mizumoto, H. Suwa, Y. Arakawa, and K. Yasumoto, "A Method for Simplified HRQOL Measurement by Smart Devices," *Wireless Mobile Communication and Healthcare*, vol. 247, pp. 91–98, 2018.
- [4] N. Jaques, S. Taylor, A. Azaria, A. Ghandeharioun, A. Sano and et al., "Predicting students' happiness from physiology, phone, mobility, and behavioral data," *Int Conf Affect Comput Intell Interact Workshops*, 2015.
- [5] S. Sonnentag, and C. Fritz, "The Recovery Experience Questionnaire: Development and Validation of a Measure for Assessing Recuperation and Unwinding From Work," *Journal of Occupational Health Psychology*, vol. 12, No. 3, pp. 204–221, 2007.
- [6] C. Binnewies, S. Sonnentag, and E. J. Mojza, "Daily performance at work: feeling recovered in the morning as a predictor of day-level job performance," *Journal of Organizational Behavior*, *J. Organiz. Behav.*, vol. 30, pp. 67–93, 2009.
- [7] W. B. Schaufeli, A. Shimazu, J. Hakanen, M. Salanova, and H. De Witte, "An ultra-short measure for work engagement: The UWES-3 validation across five countries," *European Journal of Psychological Assessment*, vol. 35, pp. 577–591, 2019.